REPORT DOCUMENTATION PAGE

Form Approved OMB NO. 0704-0188

1. REPORT DATE (DD-MM-YYYY)	2. REPORT TYPE	3. DATES COVERED (From - To)
04-09-2015	Final Report	1-Aug-2014 - 30-Apr-2015

4. TITLE AND SUBTITLE
Final Report: Compressive Imaging via Approximate Message Passing

5a. CONTRACT NUMBER
W911NF-14-1-0314

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER
611102

6. AUTHORS
Dror Baron

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES AND ADDRESSES
North Carolina State University
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8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS (ES)
U.S. Army Research Office
P.O. Box 12211
Research Triangle Park, NC 27709-2211

10. SPONSOR/MONITOR'S ACRONYM(S)
ARO

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
65803-CS-II.13

12. DISTRIBUTION AVAILIBILITY STATEMENT
Approved for Public Release; Distribution Unlimited

13. SUPPLEMENTARY NOTES
The views, opinions and/or findings contained in this report are those of the author(s) and should not contrued as an official Department of the Army position, policy or decision, unless so designated by other documentation.

14. ABSTRACT
This project considers compressive imaging problems, where images are reconstructed from as few linear measurements as possible. Compressive imaging can be applied to a broad range of applications, including medical imaging, seismic imaging, and hyperspectral imaging. We propose novel compressive imaging algorithms that employ approximate message passing (AMP), which is an iterative signal estimation algorithm that performs component-wise denoising to noisy signals. In contrast, we apply non-separable denoisers to imaging with random

15. SUBJECT TERMS
approximate message passing, compressive imaging, compressive sensing, hyperspectral imaging, signal reconstruction

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	15. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
UU	UU	UU	UU		Dror Baron
					19b. TELEPHONE NUMBER 919-513-7974

Standard Form 298 (Rev 8/98)
Prescribed by ANSI Std. Z39.18

Report Title

Final Report: Compressive Imaging via Approximate Message Passing

ABSTRACT

This project considers compressive imaging problems, where images are reconstructed from as few linear measurements as possible. Compressive imaging can be applied to a broad range of applications, including medical imaging, seismic imaging, and hyperspectral imaging. We propose novel compressive imaging algorithms that employ approximate message passing (AMP), which is an iterative signal estimation algorithm that performs
component-wise denoising to noisy signals. In contrast, we apply non-separable denoisers to imaging with random matrices and hyperspectral imaging in CASSI systems. Numerical results demonstrate that our proposed algorithms significantly improve over current state-of-the-art compressive imaging algorithms in terms of both estimation error and run-time.

Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

Received		Paper
09/04/2015	6.00	Nikhil Krishnan, Dror Baron. A Universal Parallel Two-Pass MDL Context Tree Compression Algorithm, IEEE JOURNAL OF SELECTED TOPICS IN in Signal Processing, (06 2015): 1. doi:
09/04/2015	7.00	Jin Tan, Yanting Ma, Dror Baron. Compressive Imaging via Approximate MessagePassing with Image Denoising , IEEE Transactions on Signal Processing, (04 2015): 2085. doi:
09/04/2015	5.00	Junan Zhu, Dror Baron, Marco Duarte. Recovery from Linear Measurements with Complexity-Matching Universal Signal Estimation, IEEE Transactions on Signal Processing, (03 2015): 1512. doi:
09/04/2015	8.00	Yanting Ma, Dror Baron, Deanna Needell. Two-Part Reconstruction with Noisy-Sudocodes, IEEE Transactions on Signal Processing, (12 2014): 6323. doi:

TOTAL: 4

Number of Papers published in peer-reviewed journals:

(b) Papers published in non-peer-reviewed journals (N/A for none)

Received Paper

TOTAL:

Number of Papers published in non peer-reviewed journals:

(c) Presentations

The following works were presented at conference meetings but not published in proceedings:
1. R. Fayez, J. Young, J. Tan, Y. Ma, and D. Baron, "Image Reconstriction in Radio Astronomy," Duke Workshop on Sensing and Analysis of High-Dimensional Data, Durham, NC, July 2015.
2. Y. Ma, J. Zhu, and D. Baron, "Universal Denoising in Approximate Message Passing," Duke Workshop on Sensing and Analysis of High-Dimensional Data, Durham, NC, July 2015.
3. Y. Ma, J. Zhu, and D. Baron, "Universal Denoising and Approximate Message Passing," presented at Inf. Theory Applications Workshop, San Diego, CA, February 2015.

Number of Presentations: 3.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received Paper

TOTAL:

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received		Paper
09/04/2015	9.00	Yanting Ma, Junan Zhu, Dror Baron. Compressed Sensing via Universal Denoising and Approximate Message Passing, Allerton Conference. 01-OCT-14, . : ,
09/04/2015	10.00	Jin Tan, Yanting Ma, Dror Baron. Compressive Imaging via Approximate Message Passing with Wavelet-Based Image Denoising, IEEE Global Conf. Signal Inf. Process.. 04-DEC-14, . : ,
09/04/2015	11.00	Nikhil Krishnan, Dror Baron. Performance of Parallel Two-Pass MDL Context Tree Algorithm, IEEE Global Conf. Signal Inf. Process.. 03-DEC-14, . : ,
09/04/2015	12.00	Yanting Ma, Dror Baron, Ahmad Beirami. Mismatched Estimation in Large Linear Systems, IEEE Int. Symp. Inf. Theory. 15-JUN-15, . : ,

TOTAL: **4**

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Received		Paper
09/04/2015	1.00	Jin Tan, Yanting Ma, Hoover Rueda, Dror Baron, Gonzalo R. Arce. Compressive Hyperspectral Imagingvia Approximate Message Passing, IEEE JOURNAL OF SELECTED TOPICS IN in Signal Processing (04 2015)
09/04/2015	2.00	Yanting Ma, Junan Zhu, Dror Baron. Approximate Message Passingwith Universal Denoising , IEEE Transactions on Signal Processing (06 2015)
TOTAL:		**2**

Number of Manuscripts:

Books

Received	Book
TOTAL:	

Received	Book Chapter
TOTAL:	

Patents Submitted

Compressive imaging using approximate message passing with denoising

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Patents Awarded

Awards

Graduate Students

NAME	PERCENT_SUPPORTED	Discipline
Jin Tan	1.00	
Yanting Ma	0.20	
FTE Equivalent:	**1.20**	
Total Number:	**2**	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Dror Baron	0.05	No
FTE Equivalent:	**0.05**	
Total Number:	**1**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

Number of graduating undergraduates funded by a DoD funded Center of Excellence grant for Education, Research and Engineering:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and intend to work for the Department of Defense 0.00

The number of undergraduates funded by your agreement who graduated during this period and will receive scholarships or fellowships for further studies in science, mathematics, engineering or technology fields:...... 0.00

Names of Personnel receiving masters degrees

NAME

Total Number:

Names of personnel receiving PHDs

NAME
Jin Tan (expected September 2015)

Total Number: 1

Names of other research staff

NAME	PERCENT_SUPPORTED

FTE Equivalent:
Total Number:

Sub Contractors (DD882)

Inventions (DD882)

Scientific Progress

The project made major contributions to compressive imaging. Two lines of work in compressive imaging reconstruction were pursued. The first involved 2D image reconstruction using random measurement matrices. The second involved reconstructing 3D hyper spectral image cubes, where the measurement matrices were those modeled for the well known CASSI system for compressive hyper spectral image acquisition; these CASSI matrices are highly structured.
For both lines of work, new reconstruction algorithms based on approximate message passing (AMP) significantly improve over current state-of-the-art algorithms in terms of both estimation error and run-time.

The project also indirectly contributed to the PI's research on two compressed sensing reconstruction algorithms (see the journal paper by Zhu et al. from early 2015 and the journal submission by Ma et al. from mid 2015), and another work on fast parallel algorithms for data cmpression (see the journal paper by Krishnan and Baron from mid 2015).

Technology Transfer

We have started evaluating possible technology transfer.

Final Progress Report: Compressive Imaging via Approximate Message Passing

Dror Baron – North Carolina State University

1 Introduction

This report summarizes progress made during the project "Compressive Imaging via Approximate Message Passing." Below we state the problem in Section 2, and then summarize the important results in Section 3.

2 Statement of Problem

Compressed sensing (CS) [1, 2] has sparked a tremendous amount of research activity in recent years, because it performs signal acquisition and processing using far fewer samples than required by the Nyquist rate. Breakthroughs in CS have the potential to greatly reduce the sampling rates in numerous signal processing applications such as cameras [3], medical scanners, fast analog to digital converters [4, 5], and high speed radar [6].

The intellectual foundations underlying CS rely on the ubiquitous compressibility of signals: in an appropriate basis, most of the information contained in a signal often resides in just a few large coefficients. Traditional sensing and processing first acquires the entire data, only to later throw away most coefficients and retain the few significant ones [7]. Interestingly, the information contained in the few large coefficients can be captured by a small number of random linear projections [8]. The ground-breaking work in CS [1, 2, 6] has proved for a variety of settings that the signal can then be reconstructed in a computationally feasible manner from these random projections.

Compressed sensing has been used in compressive imaging, where the input signal is an image, and the goal is to acquire the image using as few measurements as possible. Acquiring images in a compressive manner requires less sampling time than conventional imaging technologies. Applications of compressive imaging appear in medical imaging [9–11], seismic imaging [12], and hyperspectral imaging [13, 14].

As a motivating example, consider an image containing 512×512 pixels, which is roughly a quarter million pixels. We can measure the image in a compressive manner using perhaps 50,000–100,000 linear projections (20–40% of the number of pixels), and later reconstruct the original 512×512 image using some CS reconstruction algorithm. The reduction in the number of measurements is possible, because images have sparse wavelet coefficients [15], meaning that most wavelet coefficients are small in magnitude. Sparsity in the wavelet domain allows the image to be acquired and reconstructed from far fewer measurements than the total number of pixels. *Despite promising past work on compressive imaging reconstruction algorithms, there is still great potential for faster algorithms that reconstruct more precisely.*

To pursue such algorithms, we used approximate message passing (AMP) [16], which is an iterative signal estimation framework that converts a linear inverse problem, $\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{z}$, into a scalar estimation problem, $\mathbf{y} = \mathbf{x} + \mathbf{z}$, and performs scalar denoising in each iteration. The input of the scalar denoiser is a vector of noisy observations, and these observations are of the same length as the input signal vector $\mathbf{x}$. Typically, the scalar denoising function is component-wise and separable. That is, each entry of the input signal is denoised from its corresponding noisy observation. In contrast, we propose a non-separable denoiser that uses all the noisy observations to estimate each input component. The advantage of our proposed denoiser is that it makes full use of all available observations to extract information pertaining to the input signal. Therefore, our approach can estimate the input signal more accurately.

The main problem addressed in this short term innovative research (STIR) program was to significantly improve over current state-of-the-art compressive imaging algorithms in terms of both estimation error and runtime. Specific problems included:

- **Non-separable denoisers in AMP:** Bayati and Montanari have proved rigorously that AMP supports component-wise denoisers [17]. However, our results suggest that AMP succeeds in converting the matrix problem, $\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{z}$, into a scalar channel setting, $\mathbf{y} = \mathbf{x} + \mathbf{z}$, even when the denoiser is non-separable. We applied non-separable image denoisers within AMP iterations.

- **Other applications:** We expanded our denoising approaches from 2-dimensional images to 3-dimensional volumes, and applied these AMP-based reconstruction algorithms to hyperspectral imaging systems. In both the 2D and 3D cases, we significantly improved over current state-of-the-art compressive imaging algorithms in terms of both estimation error and runtime.

3 Summary of Important Results

Main results: The project studied two different compressive imaging problems. The first involved 2D images being acquired by random measurement matrices, and the second involved 3D hyper spectral image cubes acquired by a coded aperture snapshot spectral imaging (CASSI) system [18]. For both systems, we employed non-separable denoisers within AMP. For reconstructing 2D images, our algorithm [19, 20] uses an adaptive Wiener filter [21] for 2D denoising. Another option is to use a more sophisticated image 2D denoiser such as BM3D [22] within AMP.

For reconstructing 3D images [23, 24], we hoped to apply a sophisticated 3D denoiser. However, because the CASSI measurement matrix is structured and sparse, which violates the assumptions for which AMP systems were formulated, we often saw divergence effects. While others have considered various approaches to combat divergence [25, 26], the combination of a problematic matrix and complicated non-scalar 3D image cube denoiser was challenging. Eventually, we decided to use a simpler 3D denoiser, which is a simplified version of the adaptive Wiener filter [21]. This simplified denoiser combined with damping [26] helped the reconstruction algorithm converge. Reconstruction quality was typically 2–3 dB better in terms of square error than existing algorithms such as two-step iterative shrinkage/thresholding (TwIST) [27] and gradient projection for sparse reconstruction (GPSR) [28]. Additionally, the new algorithm is several times faster despite not needing to tune any parameters. In contrast, TwIST and GPSR would likely require running the algorithms several times for different parameter settings, yielding much slower reconstruction than our AMP-3D-Wiener approach. We hope that this line of work may help bring compressive hyper spectral imaging closer to practice. Indeed, we have started looking into technology transfer options. A US patent application describing these ideas was filed during the project.

Viewed in combination, our two compressive imaging reconstruction algorithms demonstrate the great promise of using non-separable denoisers in AMP. At the same time, the work on hyper spectral reconstruction highlights that the combination of a structured matrix and complicated denoisers may create divergence issues; we hope to expand our understanding of these challenges in future work.

Secondary results: The project also partly funded the PI's work on three other related research projects. Two of these involved universal algorithms for signal recovery [29–31], which estimates the input statistics on the fly from the actual noisy measurements while simultaneously recovering the input. The third involved fast parallel algorithms for data compression [32, 33].

Yet another benefit of the project was the training of doctoral students. Ms. Jin Tan was completed supported by the project during the last several months of her doctoral studies; she is expected to graduate in September 2015. Ms. Yanting Ma was partly supported for several months, and is expected to graduate in 2017.

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